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Principal component analysis of lifting waveforms

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Abstract

Background. One limiting factor in lifting research design has been the inability to effectively analyze waveform data, especially when differences in body mass, height, and load magnitude influence the derived kinetic variables. The purpose of this study was to demonstrate the sensitivity of principal component analysis to quantify clinically relevant differences in kinetic lifting waveforms over three load magnitudes and between two separate populations.

Methods. Principal component analysis was applied to five kinetic lifting waveforms. The derived principal component scores were used as the dependent measures in a two-way (clinical status × load magnitude) MANOVA.

Findings. Significant low back pain group differences ($P < 0.05$) were found for three of the principal component scores on extension moment generation in the sacral and thoracic regions and for trunk compression. Significant differences were found for each variable with respect to the magnitude across the entire lift time between the three load conditions, as well as four significant differences related to inferred mechanical changes that resulted from lifting increasingly heavier loads.

Interpretation. Principal component analysis of kinetic lifting waveforms was shown to be insensitive to a confounding factor of different load magnitudes when attempting to identify previously determined clinically relevant differences in the waveform trajectories. The analysis was able to partition the variability attributed to the direct influence of different external load magnitudes, versus those differences in spinal loading that arose from the variations in the lifting mechanics of increasing loads. The technique could be beneficial for other kinetic analyses where confounding magnitude modifiers like body size are present.
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1. Introduction

Lifting is a very complex task that requires the activation and coordination of the entire body (Chen, 2000; van Dieën et al., 1996) involving a multitude of movement strategies (Burgess-Limerick et al., 2001). When the number of muscles is compared to the mechanical degrees of freedom at the joints, it is apparent that a redundancy exists allowing the nervous system a number of options when recruiting muscles to perform a given task (Prilutsky et al., 1998). One of the limiting factors in lifting research design has been the inability to effectively analyze large amounts of waveform data, especially when differences in body mass (Marras et al., 2002), height, and load magnitude (Lavender et al., 2003) influence the derived kinetic variables. Individual lifting technique may vary considerably within a particular protocol, but differences can be difficult to detect depending on the variables selected for describing the technique (Lindbeck and Kjellberg, 2001).

Since the 1930s, manual labourers have been instructed to lift with the legs bent and back straight (squat technique) in order to minimize the chance of incurring lower back pain (LBP) (Parnianpour et al., 1987). Although the "squat" technique has been the focus of job modification in manual materials handling (MMH) industries, it is

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associated with a low compliance rate with insufficient evidence to justify using this technique over any other (van Dieën et al., 1999), while recent research (Gagnon, 2005) has questioned whether such training programs actually significantly reduce the incidence of back injuries over the long-term. As a result of differences in anthropometric measures and level of expertise with manual materials handling tasks, workers tend to modify their lifting technique in order to suit the load's physical characteristics and the nature of the task (Gagnon, 2005; Parnianpour et al., 1987).

In terms of defining a 'safe' lifting technique, researchers usually refer to compressive loading of the L5/S1 region (Scholz et al., 1995), and how this loading relates to the tissue tolerance levels for damage to the vertebral endplates (Lavender et al., 2003). Unfortunately, research investigating the influence of various loads on segmental coordination (Burgess-Limerick et al., 1995; Granata and Sanford, 2000; Scholz, 1993) has not looked at how the identified differences in coordination patterns at greater load magnitudes influence spinal loading. Such an investigation is needed to attribute how much of the increased peak flexion moment at L5/S1 is influenced by load magnitude and how much is related to the altered movement mechanics from lifting a larger load. It is also interesting to note that when research attempting to discriminate between two groups of individuals (e.g., male–female, normal-LBP) utilizing different load magnitudes, the analysis is limited to movement kinematics (Boston et al., 1993, 1995; Lindbeck and Kjellberg, 2001; Scholz et al., 1995). The problem when attempting to make group comparisons and account for influences of load magnitude or the anthropometric characteristic differences in the population from kinetic analyses is how to parse out the influences of body mass, height, and load magnitude to understand the effect of the movement mechanics. One alternative is to fix the load so that all participants are required to lift the same amount, and either use similar sized participants (Larivière et al., 2002) or a biomechanical model that can be adjusted for specific demographics (Marras et al., 2002). However, these solutions do raise another problem in that lifting research with fixed loads is based upon an a priori decision on what load to use (Larivière et al., 2000). Even when using relative loads and only assessing kinematics, the assumption is that task performance is constant at a fixed work load while Hof (1996) has suggested that even kinematic variables like acceleration should be normalized to account for the influence of gravitational acceleration.

In the area of gait analysis, research has identified that there is often a need to eliminate the confounding influence of body size on the calculation of joint moments in order to compare between two populations (e.g., clinical and 'normal'/healthy) with different anthropometric characteristics in order to identify differences in the actual walking mechanics (Hof, 1996; Moisio et al., 2003). For comparisons between genders, Moisio et al. (2003) found that normalizing to body weight times height performed better than normalizing to body weight alone, while Hof (1996) proposed that all kinematic and kinetic data be reduced to a dimensionless number that is normalized to body mass, leg length (or height depending on the context), the acceleration due to gravity, or a combination of these three parameters depending on the measure of interest. Hof (1996) goes further to state that ad hoc normalizations to body weight alone should be used cautiously due to the result in the determination of scaled variables that may not be physically sensible.

The present research proposes an alternative to normalizing kinetic parameters for group comparisons. A unique approach is proposed whereby the data reveals the differences attributed to magnitude modifiers like body mass, height, and load magnitude separately from those kinetic differences that can be attributed to differences in lifting mechanics. Using multivariate statistical techniques, the unique shape and motion of curves can be preserved (Jones and Rice, 1992). Multivariate analysis techniques have been utilized in numerous areas (Johnson and Wichern, 1992), each of which is characterized by having some need to separate and analyze the variation amongst continuous variables. One such technique that has been shown to be extremely effective in the study of human motion is principal component analysis (PCA) (Deluzio et al., 1997). PCA can be characterized by the assumption that a few dominant forms of variation can characterize most sets of data (Ramsay and Silverman, 1997). Where research like Daffertshofer et al. (2004) has demonstrated the utility of PCA in the clinical biomechanics setting for reducing the dimensionality of multivariate data sets and partitioning variant versus invariant patterns of coordination, our previous work with PCA (Wrigley et al., 2005) was able to identify group lifting kinematic and kinetic differences between healthy males who remained such over a two year follow up period versus those who developed mild LBP while employed at a nylon production facility. Furthermore, it was reported in the latter study that the identified differences would not have been discovered if a parameter-based analysis was employed (Wrigley et al., 2005). However, much like other kinetic analyses, a fixed load was employed (Larivière et al., 2002; Marras et al., 2002) with similarly sized participants (Larivière et al., 2002) in order to control for kinetic magnitude modifiers. Therefore, it is still unknown if the significant group differences for the five waveform patterns were load dependent, and to what extent the changes in movement mechanics from lifting various loads would have had on the derived kinetic measures.

By analyzing the modes of variation captured with PCA, it is possible to explore and explain specific patterns within a group of variables, as well as distinguish where two sets of data based on the same variables are different. The process identifies the parameters responsible for the greatest amount of variability in lifting technique, and partitions the variability into uncorrelated components. The purpose of this study was to demonstrate that by comparing the principal component scores derived from kinetic lifting waveforms over three load magnitudes and between two separate populations, it is possible to quantify clinically relevant differences in lifting technique, and to determine which, if any, differences are load dependent.

2. Methods

2.1. Sample data set

The analyses presented in this paper were conducted on sagittal lifts of a 5 kg, 15 kg, and 25 kg box from the floor to a shelf at shoulder height by 106 healthy males extracted from the Queen's DuPont Low Back Pain Research Study (QDLBPS) database (Stevenson et al., 2001). Below is a brief description of the study, while comprehensive details have been presented elsewhere (Stevenson et al., 2001; Wrigley et al., 2005). The database consists of both kinematic and kinetic lifting waveforms related to upper body motion along with various discrete measures describing the physical, health, and lifestyle characteristics of 35 female and 114 male participants. Subjects where included in the study if they had not reported to suffer from LBP or had not sought medical attention or had to change their regular physical activity due to LBP in the previous two year time period. As part of the testing battery, the participants were required to complete five freestyle sagittal plane lifts of three box loads (males: 5, 15, and 25 kg; females: 5, 10, and 15 kg) from the floor to a shelf at shoulder height. A FASTRAK™ motion system (Polhemus Inc, Colchester, VT, USA) was used to monitor the lifting motion with electromagnetic sensors placed on the wrist, T1 and L1 spinous processes, and the L5/S1 intervertebral space. Moments at the L5/S1 level were calculated using standard rigid body mechanics (Albert et al., 1998a,b) using Winter's (1990) anthropometric tables to calculate centre of mass and radius of gyration locations for each segment in the model. Microsoft® Access 2000 (Copyright © 1992–1999 Microsoft Corporation) was used to extract averaged curves of the five lifting trials based on the criteria that the subject was male and had successfully completed all lifts of each box load. The process yielded group sizes of 50 and 56 participants who either remained healthy over the proceeding two year period or developed mild LBP respectively. The following five kinetic waveform variables normalized to 51 time points and referenced to the proximal vertebrae about which vertebral joint interface the kinetic measures were chosen for analysis based on previous research (Wrigley et al., 2005); T1 extension moment, L1 extension moment, S1 extension moment, trunk compression, and trunk L5/S1 shear. The average lift times across each load along with the subject's age, height, and weight were also extracted.

2.2. Waveform analysis technique

Principal component analysis is based upon the assumption that most data sets can be described by a few dominant modes of variation (Ramsay and Silverman, 1997), and is accomplished through the linear transformation of correlated variables into a set of uncorrelated ones. The process involves creating matrices of waveforms such that every subject's waveform data are entered as a row vector $\underset{1\times p}{x}$ representing a single observation (individual's waveform) and p-variables (normalized time points). Each waveform can be thought of as being defined by a 51 coordinate position vector within a correlated coordinate space of normalized time points. Using this notation, each data set can be represented by the symbol $\underset{n\times p}{X}$ consisting of n-observations in p-dimensions. For the present analysis, the 50 healthy and 56 LBP group waveforms corresponding to each of the three different load magnitudes were entered as row vectors, yielding initial $\underset{318\times 51}{X}$ data matrices for each variable. The waveform data are transformed into principal components through the eigenvector analysis of either the covariance or correlation matrix. The decision to use either the covariance or correlation matrix is important, as there is no direct relationship between principal components derived using either matrix (Jackson, 1991). Jackson (1991) identifies that the correlation matrix should be used when the variables are measured in different units or are characterized by different magnitudes of variation, but the covariance matrix $(\underset{p\times p}{S})$ is more applicable for physical applications like diagnostics.

$$\underset{p\times p}{S} = \frac{\left(\underset{n\times p}{X} - \left(\underset{n\times 1}{1} \times \underset{1\times p}{\bar{x}}\right)\right)' \times \left(\underset{n\times p}{X} - \left(\underset{n\times 1}{1} \times \underset{1\times p}{\bar{x}}\right)\right)}{(n-1)} \quad (1)$$

By orthonormalizing $\underset{p\times p}{S}$, the eigenvector matrix $(\underset{p\times p}{U})$ is determined. The spread along the direction of the eigenvectors is described by the corresponding eigenvalues $\underset{1\times p}{L}$.

$$\underset{1\times p}{L} = \text{diagonal}\left(\underset{p\times p}{U'} \times \underset{p\times p}{S} \times \underset{p\times p}{U}\right) \quad (2)$$

Eigenvectors are the principal components (Troje, 2002) and can be conceptualized as a set of new variables that are used to describe the original variables. If the variables are time points, than the principal components define a new coordinate space for the original data set where the 51 coefficients are the direction cosines relating the new axes to the old. When analyzing waveforms, the series of principal component coefficients are interpreted as a single mode of variation describing variability within the entire original data set, where each mode is orthogonal to all other modes and ranked in terms of variance via the associated eigenvalue. Once $\underset{p\times p}{U}$ and $\underset{1\times p}{L}$ have been determined, it is possible to calculate a principal component score $\left(\underset{n\times p}{Z}\right)$ for each waveform with respect to each principal component using the mean value of $\underset{n\times p}{X}$ at each normalized time point $\left(\underset{1\times p}{\bar{x}}\right)$.

$$\underset{n\times p}{Z} = \left(\underset{n\times p}{X} - \left(\underset{n\times 1}{1} \times \underset{1\times p}{\bar{x}}\right)\right) \times \underset{p\times p}{U'} \quad (3)$$

The principal component scores represent the transformation of the original observations into the new coordinate space defined by the principal components. They provide a measure of distance indicating how closely each waveform conforms to the mode of variability represented by each principal component. Previous research (Hubley-Kozey and Vezina, 2002; Wrigley et al., 2005) has used the principal component scores as the dependent measure in traditional inferential statistical procedures in order to determine if there were any significant group differences. Since each of the principal components captures variability across all time points, not all 51 dimensions are required to reconstruct the original data set within a given level of accuracy. Therefore, it is possible to reduce the dimensionality of the $\underset{n\times p}{Z}$ matrix and retain only those principal component scores that reflect the 'primary' modes of variation. For the present investigation, the number of principal components retained for comparison (k) was determined using parallel analysis (Jackson, 1991; Wrigley et al., 2005). A SCREE plot was created and displays the scaled eigenvalues obtained for a single variable along with a line that represents the scaled eigenvalues from a randomly generated data set. The plotted line represents the threshold for how much variability one would expect each successive principal component to account for simply by chance. Any scaled eigenvalue that fell above this threshold line had its associated principal component and principal component score retained for analysis. An example of parallel analysis applied to the L1 extension moment variable is shown in Fig. 1. A useful property of Eq. (3) is that it can be rearranged allowing for the estimation of the original data set by adding the mean of $\underset{n\times p}{X}$ to the multiple of $\underset{n\times k}{Z}$ and $\underset{k\times p}{U}$ using the k retained principal components and principal component scores. In order to assess how well the retained principal components represent the original data, the Q-statistic ($\underset{1\times n}{Q}$) can be calculated

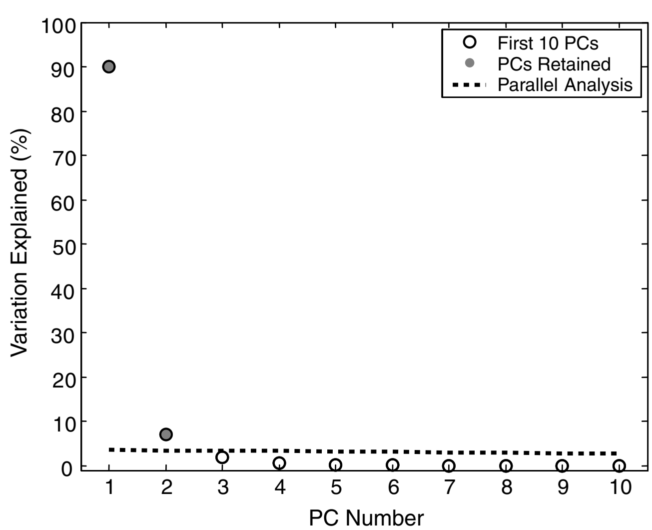

Fig. 1. A SCREE plot illustrating parallel analysis applied to the scaled eigenvalues of the first 10 principal components (PCs) for L1 extension moment. Any scaled eigenvalue that lies above the broken line representing the scaled eigenvalues from a random data set indicate those principal components that capture more variability than would be expected by chance. In this example, two principal components (●) were retained for further analysis.

$$\underset{1\times n}{Q} = \sum_{n=1}^{p}\left[\underset{n\times p}{X} - \left(\left(\underset{n\times 1}{1} \times \underset{1\times p}{\bar{x}}\right) + \left(\underset{n\times k}{Z} \times \underset{k\times p}{U}\right)\right)\right] \times \left[\underset{n\times p}{X} - \left(\left(\underset{n\times 1}{1} \times \underset{1\times p}{\bar{x}}\right) + \left(\underset{n\times k}{Z} \times \underset{k\times p}{U}\right)\right)\right]' \quad (4)$$

The Q-statistic is a sum of squares of the residuals comparing the predicted data set using the retained principal component scores and principal components with the original data. A Q-critical value (Q_α) can be calculated using a specific alpha level from a t-distribution (c_α) in order to quantify how well the data 'fit' the modes of variation captured by the retained principal components (Jackson, 1991).

$$Q_\alpha = \theta_1\left[\frac{c_\alpha\sqrt{2\theta_2 \times h_o^2}}{\theta_1} + \frac{\theta_2 \times h_o \times (h_o - 1)}{\theta_1^2} + 1\right]^{\frac{1}{h_o}} \quad (5)$$

$$\theta_1 = \sum_{i=k+1}^{p} L_i \quad (6)$$

$$\theta_2 = \sum_{i=k+1}^{p} L_i^2 \quad (7)$$

$$\theta_3 = \sum_{i=k+1}^{p} L_i^3 \quad (8)$$

$$h_o = 1 - \frac{2\theta_1 \times \theta_3}{3\theta_2^2} \quad (9)$$

Any waveform with a Q-statistic that is larger than Q-critical indicates that the waveform represents a mode of variation not captured by the retained principal components.

When assessing group differences that have been identified using PCA, the principal component scores represent the distance and direction whereas the principal components represent the location in the lift (Deluzio et al., 1997). By examining the relationship between the principal component coefficients and principal component scores, the nature of the group difference should become apparent. To assist in this interpretation, the principal component can be scaled to represent the correlation (r_{ji}) between the ith principal component and the jth time sample using the associated standard deviation (s_j) (Jackson, 1991).

$$r_{ji} = \frac{U_{ji}\sqrt{L_i}}{s_j} \quad (10)$$

By squaring the principal components scaled in this manner, the coefficients represent the proportion of variability accounted for by the principal component at each portion of the lift time.

The pattern of variation captured by each principal component is often adequately described by one of three common operators (Wrigley et al., 2005). A magnitude operator describes variation in the waveform amplitudes over the entire lift time or within a specific region; a difference operator describes a change from either having a relatively low to high waveform amplitude or vice versa; while a phase shift operator captures a change in the relative timing of waveform events. In order to assist with the interpretation of the results from PCA carried out as outlined above, it is helpful to generate representative graphs that display the mode of variation captured with original waveform trajectories to see which of the three common operators are being displayed. Previous techniques have been reported for this purpose based on selecting waveforms that coincide with a specific range of the principal component score (Jones and Rice, 1992) or based on visual inspection (Wrigley et al., 2005). In order to increase the efficiency in processing and analyzing the large amount of data for the present study, a simple optimization routine was utilized. The principal component scores were first adjusted for the amount of variability captured by multiplying each score by the ratio of the associated eigenvalue and the sum of all 51 eigenvalues when expressed as a percentage. Original waveforms corresponding to scaled principal component scores that maximized the distance to the origin of a specific principal component, while remaining as close as possible to the origin of any preceding principal components were selected. All matrix calculations were performed using MatLab (release 12.1, MathWorks Inc.).

The k principal component scores for each variable were used as the dependent measures in a two-way (clinical status × load magnitude) MANOVA in order to determine if there were any significant group differences. Box's Test of Equality of Covariance Matrices revealed that the assumption of equality of variances could not be met, although large sample sizes can result in a significant finding for this test even when the deviations are small. However, in order to help protect against Type I error, the multivariate results for Pillai's Trace were reported. Significant main effects were analyzed with Bonferroni adjusted pairwise comparisons when the variables passed a Levene's Test of Equality of Error Variances or with the Kruskal–Wallis Test when this criterion could not be met. The Mann–Whitney U Test was used to analyze any significant load effects found with the Kruskal–Wallis Test. The subject's age, height, and weight were analyzed using a one-way MANOVA to determine if there were any clinical status group differences. Significance was accepted at the $P < 0.05$ level for all statistical tests, which were performed using SPSS for Windows (Release 12.0.0, SPSS Inc).

3. Results

The PCA required either two (L1 extension moment, S1 extension moment, trunk compression) or three (T1 extension moment, trunk L5/S1 shear) principal components to account for an average of 97.53% of the variability in the five waveform variables. When each of the waveforms were reconstructed with the retained principal components, principal component scores, and the Q-statistic was calculated and compared to Q-critical, it was found that on average, 92.89% of the individual waveforms were adequately described by the principal component models ($\alpha = 0.05$).

The null hypothesis on Box's Test of Equality of Covariance Matrices was accepted for the one-way MANOVA results (Wilk's Lambda $F = 3.727, P = 0.014, \eta_p^2 = 0.099$) and post hoc analysis revealed that there was a mean difference in age between the healthy controls and LBP group (Table 1). The mean weight/height for the healthy controls and LBP groups were 83.26 kg/175.96 cm and 82.76 kg/178.48 cm respectively. Results from the two-way MANOVA revealed both significant main effects for clinical status (Pillai's Trace $F = 3.790, P = 0.001, \eta_p^2 = 0.141$) and load magnitude (Pillai's Trace $F = 21.871, P = 0.001, \eta_p^2 = 0.486$), with no significant interaction. A Levene's Test indicated that L5/S1 shear principal component one was the only variable with equal error variances, therefore the remaining principal component score variables were analyzed post hoc with the Kruskal–Wallis Test. Descriptive data for the variables found to be significantly different between the clinical status groups are presented in Table 1, while Table 2 displays the descriptive data for the variables found to be significantly different between the loading conditions.

Post hoc analysis of the clinical status main effect revealed longer lift times for the LBP group ($P < 0.05$), and significant differences for three principal component scores: T1 extension moment principal component three (4.17% of total variation), S1 extension moment principal component two (4.98% of total variation), and trunk compression principal component two (4.69% of total variation) (Table 1). As Fig. 2a shows, the greatest amount of variability in T1 extension moment is captured in two regions; between 0% and 25%, and from 30% to 60% of the lift time. Fig. 2b reveals that the relationship between the principal component coefficients and average principal component score yields a phase shift, where the T1 extension moment begins to rise relatively earlier in the lifting cycle for the LBP group. The waveform patterns captured by the latter two principal components described the LBP group's waveform trajectory adding to the average waveform until approximately 35% of the lift time when it began to start subtracting. The control group's waveform pattern was the opposite.

With respect to the load magnitude main effect, lift time significantly increased with each external load increase (Table 2), while the first principal component score was significantly different between all three combinations of the different loading conditions for each of the five kinetic variables. Not surprisingly, the first principal component extracted for all of the waveform variables was a magni-

Table 1
Group descriptive data by clinical status for variables found to be significantly different ($P < 0.05$)

Variable	Control		LBP		P[a]
	Mean	SD	Mean	SD	
Age (years)	35.08	7.94	31.11	6.13	0.005
Lift time (s)	1.80	0.36	1.92	0.51	0.026
T1 moment PC3	−7.12	47.49	6.36	47.03	0.007
S1 moment PC2	−16.70	77.52	14.91	83.17	0.002
Compression PC2	−238.06	1433.17	212.56	1419.15	0.012

Principal component labels have been abbreviated to PC#, where # denotes which principal component score had a significant group difference.
[a] Significance for all variables except age determined using the Kruskal–Wallis Test.

Table 2
Group descriptive data by external load for variables found to be significantly different ($P < 0.05$)

Variable	5 kg		15 kg		25 kg		P[a]
	Mean	SD	Mean	SD	Mean	SD	
Lift time (s)	1.69	0.31	1.83	0.38	2.07	0.55	0.001
L1 moment PC1	−296.97	132.57	15.23	170.06	281.74	210.93	0.001
L1 moment PC2[b]	12.80	52.57	−5.67	78.92	−7.14	104.72	0.040[b]
S1 moment PC1	−324.60	190.99	13.08	231.17	311.53	282.94	0.001
T1 moment PC1	−238.20	46.60	15.76	77.62	222.44	103.84	0.001
T1 moment PC2[b]	18.61	42.83	2.66	91.67	−21.28	131.52	0.001[b]
Compression PC1	−5943.74	3579.84	291.48	4204.49	5652.27	5088.03	0.001
L5/S1 shear PC1	346.52	465.53	3.63	559.90	−350.15	671.98	0.001
L5/S1 shear PC2	236.82	304.64	4.94	245.93	−241.76	346.65	0.001
L5/S1 shear PC3[b]	74.07	178.47	−24.69	165.09	−49.38	232.29	0.001[b]

Principal component labels have been abbreviated to PC#, where # denotes which principal component score had a significant group difference.
[a] Significance for all variables except L5/S1 shear PC1 determined using the Kruskal–Wallis Test.
[b] Mann–Whitney U results indicated significant differences between the 5 kg and both the 15 kg and 25 kg load conditions, but not between the 15 kg and 25 kg load conditions.

tude operator across the entire lift time (Figs. 3–7). Fig. 3a displays both the original coefficients of the first principal component for L1 extension moment (90.06% of total variation) as well as the coefficients scaled to the percentage of variation accounted for. When the sign of the mean principal component scores are examined (Table 2), it becomes apparent that the negative sign for the 5 kg load condition is indicative of the waveform subtracting from the mean waveform across the entire lift time, the positive and relatively small score for the 15 kg load condition will lead to the waveform adding to the mean waveform but remain relatively close, while the positive and relatively large score for the 25 kg load condition will result in the waveform adding to the mean waveform across the entire lift time. This pattern of variability consistently accounts for approximately 80–95% of the variation in L1 extension moment across the lift, resulting in a stratified difference in magnitude between the three loading conditions (Fig. 3b).

An almost identical pattern was captured by both S1 extension moment and trunk compression principal component one (91.89% and 92.94% of total variation respectively), with the relative amount of variation captured ranging from approximately 70% to 98% for the first variable (Fig. 4a), and between approximately 80% and 98% for the second (Fig. 5a). These patterns of variation again resulted in a magnitude difference between the loading conditions that was fairly consistent across the entire lift time (Figs. 4b and 5b). However, the magnitude operator for T1 extension moment principal component one (77% of total variation) only accounted for approximately 25% of the variation until about 40% of the lift time, when it rose to over 90% of the variation by 55% of the lift time (Fig. 6a). Opposite to this, L5/S1 shear principal component one (68.96% of total variation) loaded greatest (approximately 85% of the variation) until about 35% of the lift time, when it dropped dramatically until there was little to no variation accounted for after 80% of the lift time (Fig. 7a). Unlike the three previous magnitude differences, the preceding two patterns of variation lead to an inconsistent magnitude difference between the loading conditions across the lift time (Figs. 6b and 7b).

The key benefit of PCA for the current analysis was the ability to partition the variability within the waveforms into uncorrelated components. Once the magnitude operator of load magnitude was removed with the first principal component, there were four significant group differences between the three loads related to differences in movement mechanics introduced by the individual loading conditions (Figs. 8–11). Three difference operators were captured by the T1 moment, L1 moment, and L5/S1 shear principal component two variables (17.26%, 6.99%, and 21.87% of

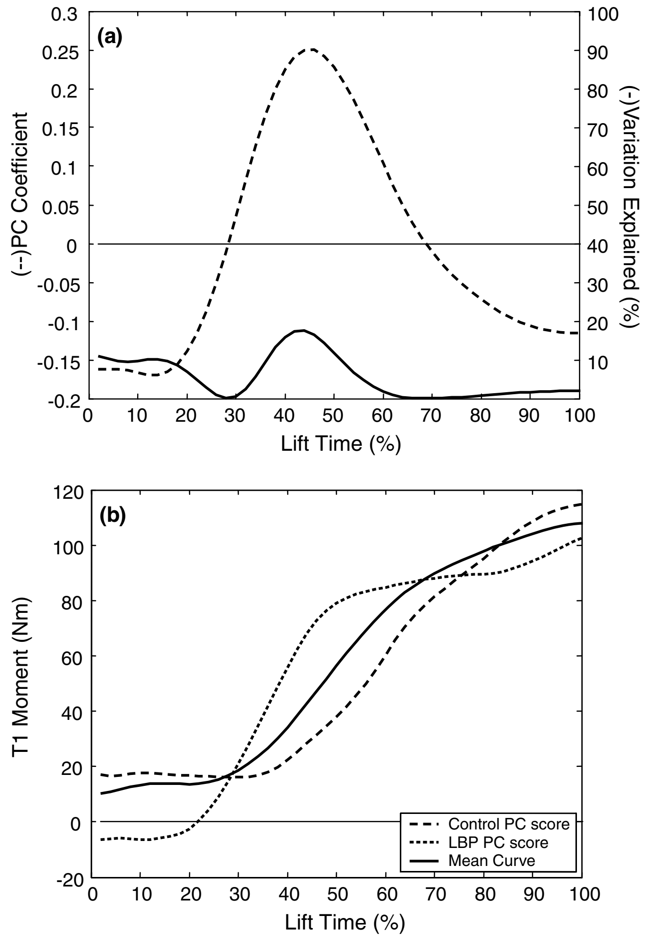

Fig. 2. (a) The original coefficients of T1 extension moment principal component three (---) and the coefficients scaled to the percentage of variation explained (—). (b) The positive mean principal component score for the LBP group causes the representative waveform to subtract from the mean curve when the coefficient is negative, and add when the coefficient is positive. Principal component labels have been abbreviated to PC.

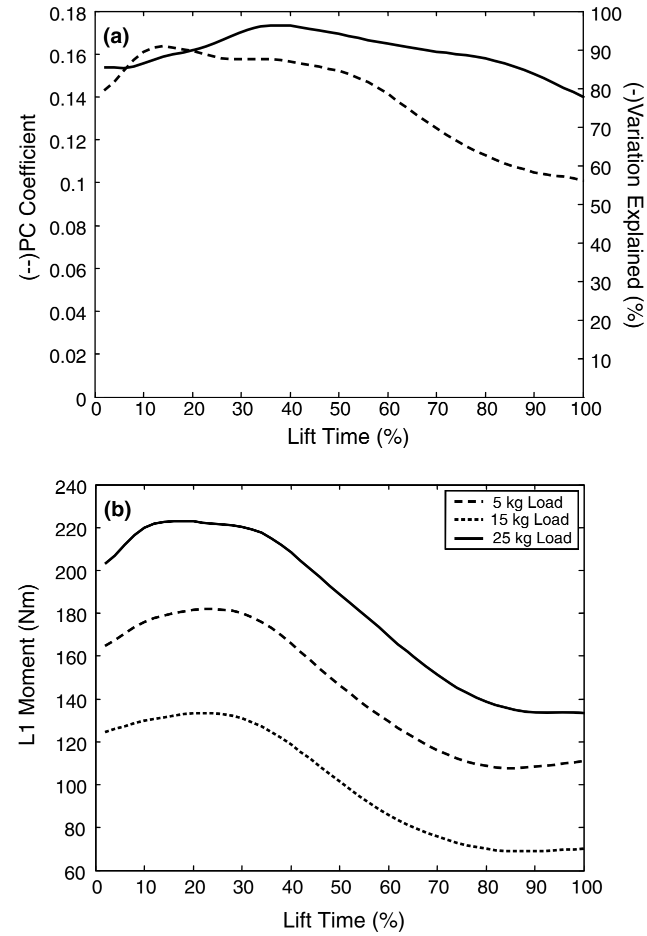

Fig. 3. (a) The original coefficients of L1 extension moment principal component one (---) and the coefficients scaled to the percentage of variation explained (—). (b) The large amount of variation consistently accounted for across the entire lift time results in a fairly consistent magnitude difference between the three loading conditions.

total variation respectively), while L5/S1 shear principal component three (6.84% of total variation) depicted a phase shift. Analysis of the waveform pattern captured by T1 extension moment principal component two revealed that the 5 kg condition added to the average waveform until approximately 50% of the lift time when it began to subtract (Fig. 8). The same loading condition for L1 extension moment principal component two elicited a similar pattern that switched to subtracting from the mean curve again around 50% of the lift time (Fig. 9). Both the 15 kg and 25 kg conditions resulted in patterns of variation opposite in direction for both the T1 and L1 extension moment principal component two variables.

As for the significant load condition difference on the second principal component for the L5/S1 shear variable, the 5 kg condition subtracted from the mean curve until approximately 30% of the lift time when it began to add, the 15 kg condition remained close to the mean curve, while the 25 kg condition first added to the mean curve until around 30% of the lift time when it began to subtract (Fig. 10). These differences in the L5/S1 shear loading pattern are reflected by the magnitude of the mean principal component score (Table 2). With respect to the second principal component for L5/S1 shear loading, the 5 kg condition was relatively large and positive, the 15 kg condition was relatively close to zero, and the 25 kg condition was relatively large and negative. Finally, the significantly different pattern captured by L5/S1 shear principal component three revealed that for the 5 kg loading condition, the waveform trajectory began to drop relatively sooner in the lift time as compared to the 15 kg and 25 kg conditions (Fig. 11).

4. Discussion

The unique approach of allowing a confounding factor of different load magnitudes to remain within un-scaled or normalized kinetic waveform variables during a comparison between similarly sized participants was assessed. It was found that the influence of the different loads on

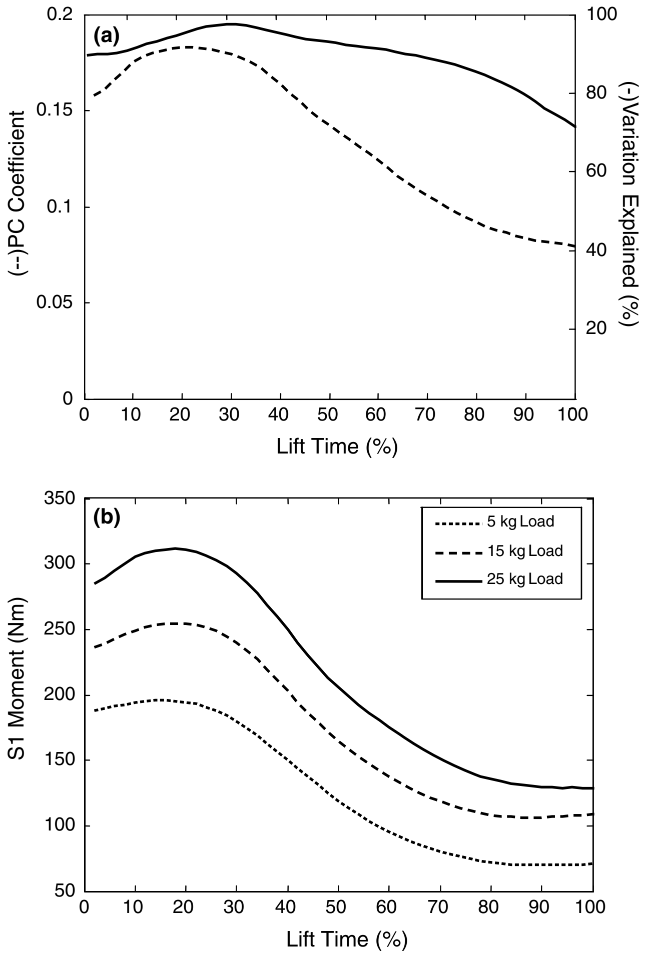

Fig. 4. (a) The original coefficients of S1 extension moment principal component one (---) and the coefficients scaled to the percentage of variation explained (—). (b) The large amount of variation consistently accounted for across the entire lift time results in a fairly consistent magnitude difference between the three loading conditions.

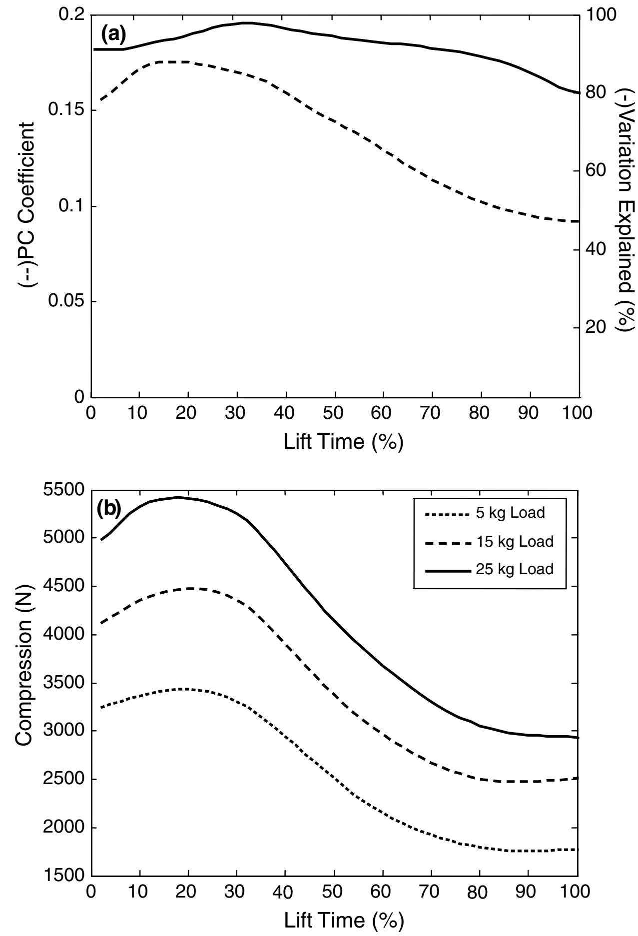

Fig. 5. (a) The original coefficients of trunk compression principal component one (---) and the coefficients scaled to the percentage of variation explained (—). (b) The large amount of variation consistently accounted for across the entire lift time results in a fairly consistent magnitude difference between the three loading conditions.

the magnitude of the kinetic variables did not affect the sensitivity of identifying previously determined (Wrigley et al., 2005) clinically relevant differences in the waveform trajectories. Not only did the confounding factor not modify the results, it further enhanced our understanding of the LBP group differences by identifying that they were not load dependent. Furthermore, the analysis was able to partition the variability attributed to the direct influence of different external load magnitudes for all five kinetic variables, versus those differences in spinal loading that arose from the variations in the lifting mechanics of increasing loads. Finally, PCA was able to identify that the magnitude operator introduced by the three different loading conditions did not account for a consistent amount of variability across the entire lift time for all of the variables, bringing into question the practice of normalizing kinetic waveform data to a scalar value for between group comparisons.

Our previous research (Wrigley et al., 2005) attributed the relationship between the LBP group differences for the T1 extension moment principal component three and S1 extension moment principal component two variables to an extension moment transfer phenomenon. The LBP group tended to shift the moment generation in the back from the L5/S1 interface to the thoracic region at around 30–35% of the lift time. Larivière et al. (2002) reported that a chronic LBP group increased thoracic erector spinae activation with a concomitant reduction in lumbar erector spinae activation during a lifting task. Unlike Larivière et al. (2002), Wrigley et al. (2005) and the present study identified these associated patterns in healthy males prior to the development of LBP, leading to conclusion that a drop in the S1 extension moment accompanied by a rise in the T1 extension moment during the first third of a lift is most likely not related to a protective mechanism whereby individuals with LBP are compensating for lumbar pain. Rather, it appears that the aberrant pattern is present prior to the manifestation of lumbar pain, and is possibly a precursor or may even be an indicator of LBP development. As with the our previous study (Wrigley et al., 2005), a related pattern of trunk compressive unload-

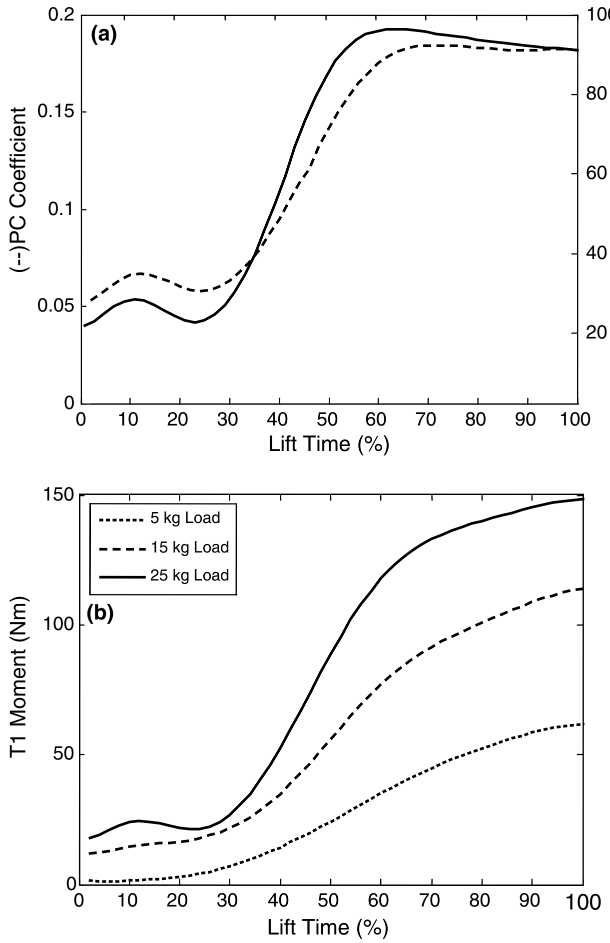

Fig. 6. (a) The original coefficients of T1 extension moment principal component one (---) and the coefficients scaled to the percentage of variation explained (—). (b) The inconsistency in the amount of variation accounted for across the entire lift time results in a larger magnitude difference between the load conditions over the last half of the lift.

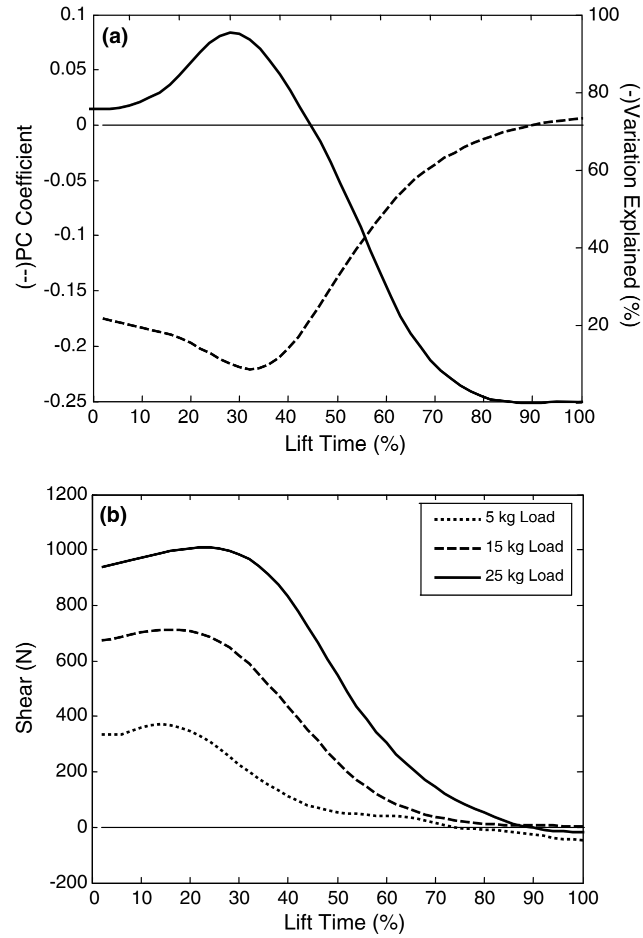

Fig. 7. (a) The original coefficients of L5/S1 shear principal component one (---) and the coefficients scaled to the percentage of variation explained (—). (b) The inconsistency in the amount of variation accounted for across the entire lift time results in a larger magnitude difference between the load conditions for the first two thirds of the lift.

ing was found that reflected the clinical status group difference for S1 extension moment principal component two.

Perhaps one of the greatest advantages to using PCA for analysing lifting waveforms is the inherent ability to partition the variability into uncorrelated components for further analysis without the need for any a priori decisions on how to group or reduce the data. Our previous study (Wrigley et al., 2005) was able to demonstrate that by reducing waveform trajectories into summary variables like the maximum value, the sensitivity of subsequent hypothesis testing is critically compromised and clinically relevant group differences may be lost entirely (Albert et al., 1998a,b; Larivière et al., 2002). Furthermore, the present study was able to not only confirm the previous results but was also able to show how magnitude modifiers like various loading conditions can be analyzed without normalization for the comparison between two groups of individuals. Such an approach would not only aid research seeking to discriminate between healthy controls and those with LBP (Boston et al., 1993, 1995; Larivière et al., 2000, 2002; Scholz et al., 1995), but can also be applied to the study of how different loading conditions influence movement coordination and the resultant impact on kinetic measures (Burgess-Limerick et al., 1995; Granata and Sanford, 2000; Scholz, 1993), as well as investigating the influence of gender on trunk kinematics and spinal loading (Lindbeck and Kjellberg, 2001; Marras et al., 2002, 2003; Stevenson et al., 1996).

In terms of the influence load magnitude has on the lifting movement mechanics, Burgess-Limerick et al. (1995) reported a consistent distal-to-proximal coordination pattern with respect to knee, hip, and lumbar extension phase angles during freestyle lifting that increased in relative phase lag with increases in load magnitude, while Granata and Sanford (2000) reported an increase in the lumbar contribution with respect to pelvic motion in total trunk motion with increases in load. Furthermore, Scholz (1993) identified significant load magnitude effects for five permutations of relative phase angle combinations between the ankle, knee, hip, and back phase angles. However, none of these studies reported or assessed how the differences in movement mechanics that were identified with changes in

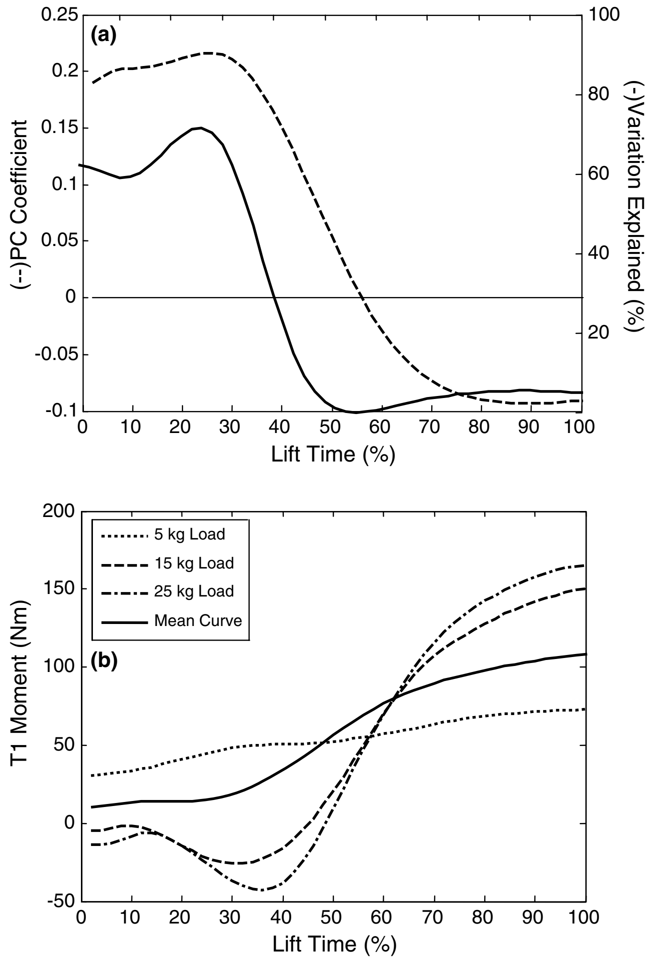

Fig. 8. (a) The original coefficients of T1 extension moment principal component two (---) and the coefficients scaled to the percentage of variation explained (—). (b) A difference operator is captured where the waveform representing the 5 kg condition adds to mean curve until around 50% of the lift time when it begins to subtract. The statistically equivalent mean principal component scores between the waveforms representing the 15 kg and 25 kg load conditions leads to these waveforms exhibiting similar patterns that are in opposite direction to that of the 5 kg load condition waveform.

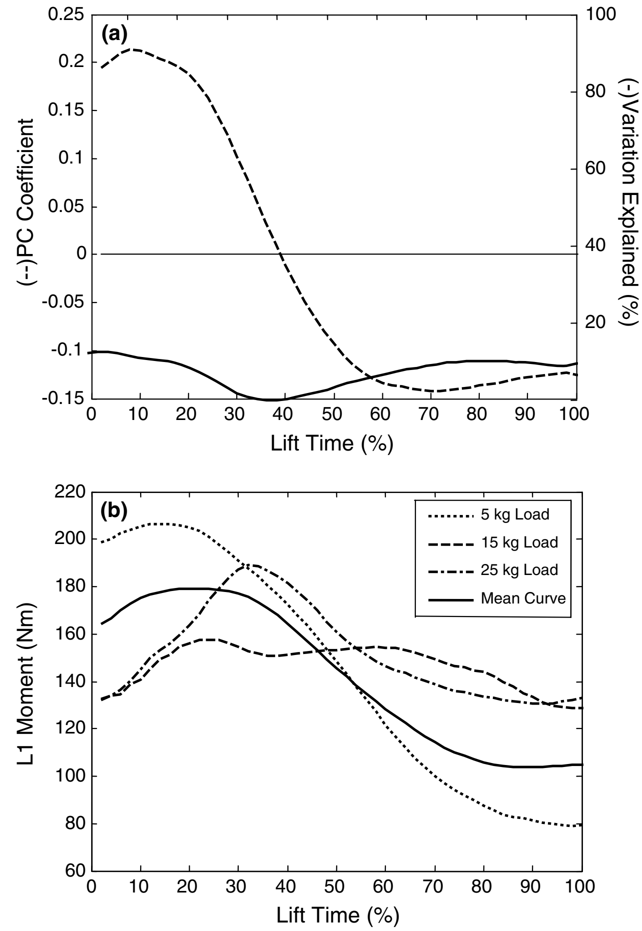

Fig. 9. (a) The original coefficients of L1 extension moment principal component two (---) and the coefficients scaled to the percentage of variation explained (—). (b) A difference operator is captured where the waveform representing the 5 kg condition adds to mean curve until around 50% of the lift time when it begins to subtract. The statistically equivalent mean principal component scores between the waveforms representing the 15 kg and 25 kg load conditions leads to these waveforms similarly acting in the opposite direction to that of the 5 kg load condition waveform.

load magnitude would ultimately influence spinal loading after the direct influence of different load magnitudes was removed. In the present study, once the magnitude operator introduced by the three load conditions was accounted for and removed with the first principal component on all five kinetic variables, four kinetic waveform patterns of variability were found to be significantly different between the conditions. The second principal component for the T1 and L1 extension moments along with trunk L5/S1 shear captured difference operators, while trunk L5/S1 shear principal component three captured a phase shift. Although the changes in movement mechanics as the load magnitude was varied were not assessed in the present study, previous research (Burgess-Limerick et al., 1995; Granata and Sanford, 2000; Scholz, 1993) has consistently identified that changes do exist, and it is assumed that they were present with the current participants. Under this assumption, it is interesting to note that 'safe' lifting technique usually refers to compressive loading of the L5/S1 region (Scholz et al., 1995), yet the presumed changes in movement mechanics with the increase in load magnitude resulted in significantly different patterns of variability for two L5/S1 shear variables, and not trunk compression. Increases in load magnitude will increase the overall compression experienced in the lumbar region, but the associated changes in movement mechanics have a greater influence on T1 and L1 extension moments, and L5/S1 shear loading.

An unexpected but interesting result from the PCA was that the magnitude operator introduced by the three different loading conditions did not account for a consistent amount of variability across the entire lift time for all of the variables. Although it is often common and accepted practice to normalize kinetic variables to a scalar quantify that accounts for different anthropometric characteristics

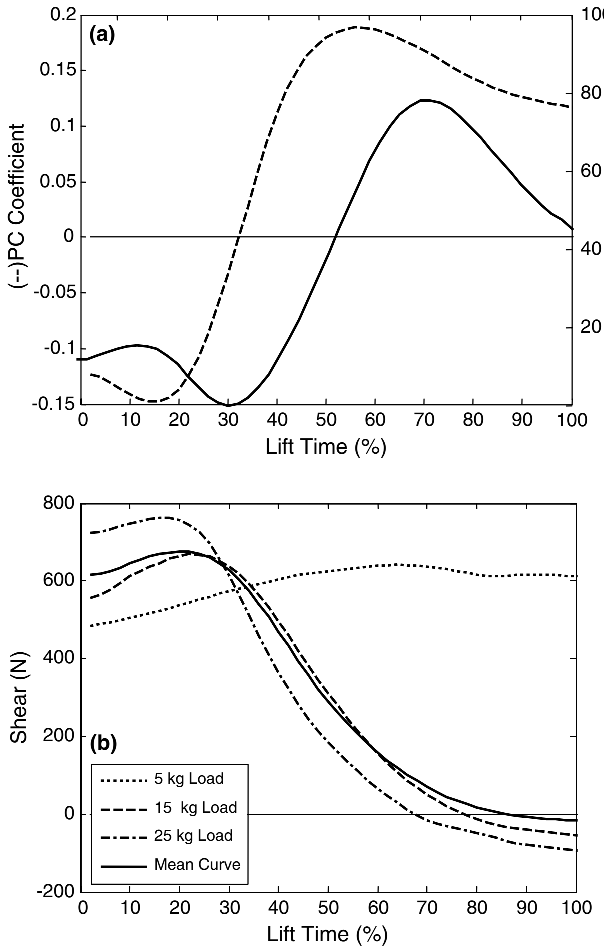

Fig. 10. (a) The original coefficients of L5/S1 shear principal component two (---) and the coefficients scaled to the percentage of variation explained (—). (b) The relatively large and positive mean principal component score for the 5 kg condition lead to the corresponding waveform subtracting from the mean curve until approximately 30% of the lift time when it began to add. On the other hand, the corresponding mean principal component score for the 15 kg condition was relatively close to zero leading to that waveform remaining close to the mean waveform. Finally, the mean principal component score for the 25 kg condition was relatively large and negative thereby resulting in the representative waveform first adding to the mean curve until around 30% of the lift when it began to subtract.

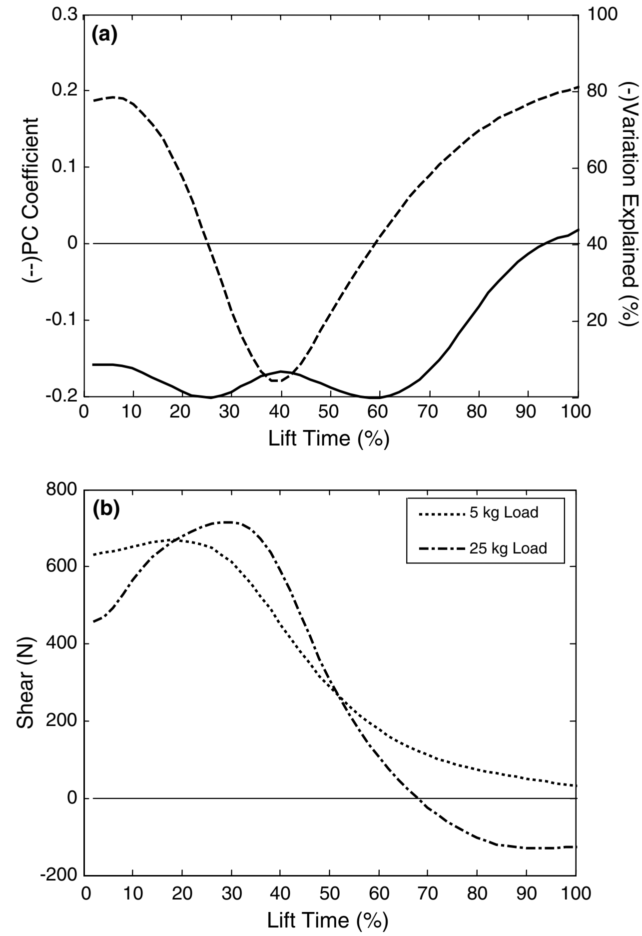

Fig. 11. (a) The original coefficients of L5/S1 shear principal component three (---) and the coefficients scaled to the percentage of variation explained (—). (b) A phase shift is captured where the shear loading pattern for the 5 kg condition begins to fall relatively sooner in the lift as compared to both the 15 kg and 25 kg conditions. The representative waveforms for the 15 kg condition and mean trajectory have been omitted due to their proximity to the waveform representing the 5 kg condition.

(Moisio et al., 2003; Schipplein et al., 1990) or load magnitude (Freivalds et al., 1984) for the purpose of comparing between groups of individuals or previously published findings, Hof (1996) has suggested that this is not fundamentally sensible. The results from the present study further support Hof (1996), and reflect the need for dynamic scaling of the waveform data that can account for how much variability is introduced by magnitude modifiers like load magnitude at each portion of the lifting motion prior to reducing the curve into summary variables. As identified earlier, the reduction of waveform trajectories into summary variables can decrease the sensitivity of subsequent hypothesis testing, while the further scaling of this already drastically reduced data by a fixed factor like body weight times height could only further confound hypothesis testing and may not actually reflect mechanically relevant variables. Further investigations are warranted into this area.

5. Summary

The influence of three different load magnitudes on the ability to identify clinically relevant differences in lifting technique using PCA of lifting waveforms was assessed. There were four main findings in this study; (1) the variability introduced to the five kinetic variables by the different load magnitudes did not decrease the sensitivity of PCA for identifying significant clinical status group differences, (2) the significant group differences were not load dependent, (3) PCA partitioned the variability into uncorrelated components which allowed the assessment of how the load magnitude itself effected the magnitude of the kinetic variables as well as how inferred changes in the movement mechanics due to lifting larger loads influenced the same variables, and (4) the variability introduced by the different load magnitudes was not consistent across the entire lift time for all five variables. The application of PCA to lifting waveforms has been shown to be a sensitive tool for identifying and describing clinically relevant group differences between males who remain healthy versus those who developed LBP while employed in a manual materials handling industry. Further research utilizing waveform analysis is warranted into other areas like gender differences in spinal loading in order to increase our understanding of the development of lumbar pain and possible biomechanical risk factors that can lead to chronic LBP.

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